CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

Project Start Date: September 2017
Project End Date: May 2018
April 2020

On Transportation Equity Implications of Connected and Autonomous Vehicles (CAV)

A Review of Methodologies

by
Tierra S. Bills
Assistant Professor
Wayne State University

DISCLAIMER

Funding for this research was provided by the Center for Connected and Automated Transportation under Grant No. 69A3551747105 of the U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology (OST-R), University Transportation Centers Program. The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Suggested APA Format Citation: Bills, T (2020). On Transportation Equity Implications of Connected and Autonomous Vehicles (CAV) A Review of Methodologies. Final Report. USDOT CCAT Project No. 5.

Identifier:

Contacts

For more information:

Tierra Bills
5050 Anthony Wayne Drive
Detroit, MI 48202
Phone: 313-577-7918
Email: tbills@wayne.edu

CCAT
University of Michigan Transportation Research Institute
2901 Baxter Road
Ann Arbor, MI 48152
umtri-ccat@umich.edu
(734) 763-2498

Technical Report Documentation Page

<table>
<tr><td>1. Report No.</td><td>2. Government Accession No.
Leave blank – not used</td><td>3. Recipient's Catalog No.
Leave blank - not used</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle
On Transportation Equity Implications of Connected and Autonomous Vehicles (CAV): A review of Methodologies</td><td>5. Report Date
Enter same date as is on the report cover. Enter full publication date, including month and date, if available, and full year. Example: June 5, 2014 or June 2014 or 2014</td></tr>
<tr><td>6. Performing Organization Code
Enter any/all unique numbers assigned to the performing organization, if applicable.</td></tr>
<tr><td colspan="2">7. Author(s)
Tierra Bills, PhD http://orcid.org/0000-0002-2899-8031
Tian Tian, MSUP</td><td>8. Performing Organization Report No.
CCAT Project No. 5</td></tr>
<tr><td colspan="2" rowspan="2">9. Performing Organization Name and Address
Center for Connected and Automated Transportation
University of Michigan Transportation Research Institute
2901 Baxter Road
Ann Arbor, MI 48109.</td><td>10. Work Unit No.</td></tr>
<tr><td>11. Contract or Grant No.
Contract No. 69A3551747105</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Agency Name and Address
U.S. Department of Transportation
Office of the Assistant Secretary for Research and Technology
1200 New Jersey Avenue, SE
Washington, DC 20590</td><td>13. Type of Report and Period Covered
Enter the type of report (e.g. final, draft final, interim, quarterly, special, etc.) followed by the dates during which the work was performed. Example: Final Report (June 2012-June 2014)</td></tr>
<tr><td>14. Sponsoring Agency Code
OST-R</td></tr>
<tr><td colspan="3">15. Supplementary Notes
Conducted under the U.S. DOT Office of the Assistant Secretary for Research and Technology's (OST-R) University Transportation Centers (UTC) program.</td></tr>
</table>

CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

16. Abstract

This review brings together the bodies of literature on transportation equity analysis, travel behavior forecasting, and impacts of CAVs, with the ultimate objective of highlighting important research needs for measuring the transportation equity implications of CAVs. In comparison to previous reviews of social impacts of CAV our focus is specifically on the state of current methods for accessing the transportation equity implications of CAVs. We seek to provide a summary of the methods used to assess potential impacts of CAV's and how these impacts are likely to apply for transport disadvantaged communities. Our review highlight some critical gaps in available methods for measuring potential equity impacts of CAVs. We find that Our while a range of methods exists that may be applied to begin building our understanding of CAV equity implications, clear guidance how to appropriately apply these is warranted.

17. Key Words	18. Distribution Statement
Transportation Equity, Connected and Autonomous Vehicles, Transportation Planning, Methods	No restrictions.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	16	Leave blank – not used

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

Table of Contents

1. Introduction

1.1.Motivation and Overview

Transportation researchers and industry experts predict that fully self-driving and connected vehicles will transform transportation systems as we know them today; alleviating traffic accidents and traffic delay, enabling new and more far reaching transportation alternatives for all. However, little discourse and study has centered on the potential equity impacts and adverse impacts to disadvantaged/ financially constrained members of society. These are individuals for whom automobiles are not affordable and/or who struggle to access reliable transit (i.e. low income, elderly, and disabled households). As with many transformative transportation innovations of the past – such as the Eisenhower Interstate System - the entrance of CAV technologies in the market may generally result in benefits to the larger society, but at the expense of financially constrained, transport disadvantaged communities. The risk here is that these financially constrained communities will be largely priced out of the benefits of CAV benefits, and if we continue towards developing CAV technologies and services without considering the equity implications for disadvantaged members of society, we will continue to allow or support patterns of decline, exclusion, and underemployment among society.

Emerging transportation technologies range from web and app-based navigational tools to full automation (level-5) connected and autonomous vehicles (CAVs) (See Cassetta et. al 2017 for a broader discussion). In this paper, the emphasis is broadly on levels 4 and 5 automation and the range of technologies (e.g. sensors, data collection systems, advanced machine learning algorithms, etc.) that support them. The proposal at the center of this study is that transportation planners require tools for forecasting the equity impacts of fully autonomous CAVs with accompanying business models (i.e. single ownership vs. group subscription/ car sharing).

A number of recent reports highlight the urgency of understanding the equity implications of CAV's for different communities, as impacts are expected to differ for people of different age groups, levels of ability, race and ethnicity, income levels, and so on (Ricci, 2019). Nevertheless, a growing number of metropolitan planning organizations are including emerging transportation technologies (like CAV's) in their regional transportation plans, without considering the equity implications of these technologies. A study by Kuzio (2019) found that 70% of MPO's mentioned CAV's and other emerging transportation technologies in their regional plans, but only 20% consider the equity implications of these technologies. Further, none seem to have attempted measuring these potential impacts.

This review brings together the bodies of literature on transportation equity analysis, travel behavior forecasting, and impacts of CAVs, with the ultimate objective of highlighting important research needs for understanding the transportation equity implications of CAVs. In comparison to previous reviews of social impacts of CAV (e.g. Litman, 2017, and Ricci, 2019) our focus is specifically on the state of current methods for accessing the transportation equity implications of CAVs. We seek to provide a summary of the methods used to assess potential impacts of CAV's and how these impacts are likely to apply for transport disadvantaged communities. Our review highlight some critical gaps in available methods for measuring potential equity impacts of CAV.

1.2. Definitions of Transportation Equity

While terms such as transportation equity, social equity, social justice, environmental justice, social inclusion, etc. have a commonplace in the transportation planning and policy literature, researchers and practitioners still struggle with a consistent and practical framework to understand and apply principles of transportation equity. There are a number of studies that use "equity" as synonymous to 'fairness' attempt to measure "equity impacts" of transportation decisions, but few studies take the additional step of identifying rules for defining what distribution of costs/benefits is considered "fair", and measure the extent to which the impacts satisfy these rule.

For this reason, we adopt a framework for organizing definitions of transportation equity used in Bills and Walker (2017). This framework segments the definition of transportation into a general equity concept, equity dimensions, and equity standards.

The general *concept*, and perhaps the more widely agreed-on definition, refers to the fair or just distribution of transportation costs and benefits, among members of society. The costs can range from trip-based costs or fares or increases in travel time to more abstract costs like consumer surplus, emissions, noise pollution, etc. Similarly, benefits may be reductions in trip costs and travel times, improvements in accessibility, etc. Beyond the general concept, transportation equity can be defined along two primary *dimensions*: Horizontal and Vertical equity (Musgrave and Musgrave, 1989; Litman, 2002). Horizontal equity, which may include spatial and generational equity, refers to the distribution of impacts for groups that are considered to be equal in ability and need. Vertical equity refers to the impacts on groups that differ in ability and needs, such as different social and income classes. Finally**,** there exists a number of competing equity *standards*, which represent alternative ideas of what distribution (regarding rights, opportunities, resources, wealth, primary goods, welfare, utility, etc.) is considered as *fair* or most desired.

Transportation equity analysis refers to a range of processes and tools for estimating how vulnerable communities will likely be affected by proposed transportation investments. The most equity analysis processes include some combination of the following steps:

> **Comparison groups**: It is necessary to define the groups to be compared, with some group(s) representing vulnerable communities (e.g. low income, minority, 0-auto ownership, disabled, and elderly) and some group(s) representing more affluent communities (e.g. high income and 1+ auto ownership). These groups can be segmented at the zonal level (e.g. defining the vulnerable group by all residential zones with high concentrations of low income and minority households). On the other end of the spectrum, groups can be segmented at the individual level. While the zonal level segmentation may be more convenient in some cases, individual segmentation can provide a more accurate picture of how the groups are impacted (Bills and Walker, 2017).
>
> **Equity indicators:** A set of equity indicators are selected to measure costs and benefits that result from the transportation investment being assessed. Some typical measures are income travel time, job accessibility, and emissions levels. (SANDAG, 2011; MTC 2013a). For a more extensive review of equity indicators, see Litman (2002) and DiCiommo and Shiftan (2017).
>
> **Calculate Results:** A critical step in the analysis is to apply the equity indicators to measure the effects of the proposed transportation investment. This involves the use of extrapolation tools to forecast how circumstances (as represented by the indicators) will change, due to the investment (for example see Rodier et al., 2001 and Castiglione et al., 2006). While there are a number of approaches to modeling these effects, we highlight the use of travel demand models, as they are uniformly available for metropolitan planning organizations and conventional tools for forecasting likely impacts of proposed transportation investments.

2. Literature Review

A review of the literature on measurement of potential impacts of connected and autonomous vehicles suggests there are three critical phases or groups of relevant questions : 1) short term (Adoption), 2) mid-term (travel behavior change), and 3) long term impacts (e.g. emissions reductions, land-use-related changes, job loss/ growth, etc.). There is a clear expectation around high level benefits to expect (Litman, 2017). However, the future distribution of these benefits across the population is much less certain. They require a better understanding of adoption patterns and how these will change over time, how travel behaviors can be expected to change and how this might vary for more vulnerable communities, and longer term effects, which may be more severe for vulnerable communities. For these reasons, we organize our review into three parts, corresponding with the three groups of questions outlined above. For each part, we will emphasize what has been done to understand equity implication, a review of the core methods, and provide a critique of the methods.

2.1. Adoption

Critical questions related to the first set of questions - the adoption rate of CAVs over time - have arguably received the most attention in the transportation science and planning literature to date, compared to questions of travel behavior change and long term impacts. The focus of such studies has largely been on the most likely initial responses to CAVs in the market, such as acceptance and expected adoption rates among society. The most popular research approach seems to be some form of stated preference survey, coupled with estimating willingness-to-pay measures as a function of socio-demographics, attitudinal variables, current travel behaviors, etc. Here we start with a discussion of studies that seek to address equity implications of CAV adoption and utilization, then we review the basics of willingness-to-pay methods used to forecast the adoption and utilization of CAV's. We then provide a summary of findings and offer a critique of the approach.

2.2. Adoption of Connected and Autonomous Vehicles and Equity

Regarding equity implications, there has been limited analysis on how the rates of adoption and utilization may differ for transport disadvantaged communities. There are a few noteworthy mentions. A study by Nordhoff et. al. (2016) highlights equity and inclusion as an indicator of CAV acceptance. They state that "The inclusion of equity as the distribution of costs and benefits among affected parties is important. Including equity provides valuable insights when (penetration level) users would adopt driverless vehicles and for whom they would be the most beneficial". Vlassenroot and Brookhuis (2014) also confirm that equity is an important indicator of the acceptance of intelligent transportation technologies. Although these papers highlight a potential connection between equity and acceptance of CAV, no studies are found to have taken additional steps to address how adoption and utilization rates are likely to differ for transportation disadvantaged communities.

2.3. Methods and Individual Study Findings

As previously mentioned, efforts to understand the potential adoption patterns of CAVs have largely applied a mix of stated preference surveys and Willingness to Pay (WTP) measures. Willingness to pay is a money measure of welfare and conceptually refers to the maximum price a consumer is willing to pay for a good or policy change (Just et. al. 2005). Willingness to Pay can be estimated using a range of experimental and market experience settings. As CAVs are not yet on the market, it is understandable that the most relevant to the assessments in this case are those measurement approaches using an experimental setting (for more on measuring willingness to pay, see Breidert et al., 2015).

Our review of the literature on prediction of CAV adoption patterns shows that the primary approach used to elicit people's WTP is contingent valuation (CV), while a fewer number of studies apply conjoint analysis (CA). With contingent valuation, survey participants were asked directly to report their WTP to purchase or use CAVs and included transportation automation technologies. (Schoettle and Sivak, 2014; Kyriakidis et al., 2015; Bansal et al., 2016). On the other hand, conjoint analysis is based on the assumption that money values (such as WTP) cannot be measured directly and must be inferred by recording choices from among a set of alternatives (Marder, 1999), or stated preference experiment.

Our review finds a number of well cited previous studies which have applied contingent valuation to measure willingness to pay for CAV, however each with a slightly different focus:

- Schoettle and Sivak (2014) investigate people's WTP for Level 4 automation in the United States, the United Kingdom, and Australia. The demographic variables collected from respondents include age, gender, education level and employment status. They found that while as much as 59% of respondents had a WTP of $0 (in the US), 10% of respondents in the US were willing to pay at least $5800, while 10% in the UK and Australia were willing to pay at least $9,400 for level 4 automation.
- Kyriakidis el al. (2015) collected a survey of 5000 responses, representing 109 different countries, in order to estimate a WTP for partially automated driving, highly automated driving and fully automated driving. Demographic variables collected in this survey were age and gender. They found that while 22% or respondents had a WTP of $0, 5% had a WTP of more than $30,000 for a fully automated driving system.
- Bansal et al. (2016) investigated individuals WTP for level 3 and level 4 CAV automation in Austin, Texas. Note that level 3 automation refers to partial self-driving capabilities, while level 4 automation refers to full driving

automation with the option for a human driver to request and access control (NHTSA, 2013). Based on a sample of 347 respondents from an internet based survey, they estimated an average WTP of $7253 for level 4 automation and $3300 for level 3 automation. Their survey included demographic variables such as age, gender, and education level. They found that respondents who are male, technology savvy, had more children, and traveled more were more likely to have a higher WTP for automation technologies.

- Bansal and Kockelman (2017) focused on people's current WTP for different levels of automation (level1 to level 4) as well as distinct features of CAVs. These features included lane centering, left turn assist, pedestrian detection, adaptive cruise control, sign recognition, and more. Overall, they found that 39% of respondents had a WTP of $0, they estimated an aggregate WTP of $5470 for level 3 automation and $14,196 for level 4 automation, for those who had some level of WTP.
- Liu et. al. (2019) conducted a survey in two cities; Tianjin and Xi'an China. Their focus was on estimating how WTP for CAVs differs across certain demographics (age, gender, education level, and income) and psychological characteristics (perceived benefit and risk, perceived dread, and trust in full automation vehicles). Their survey included 1355 respondents in total, and their analysis involved testing the predictive power of each demographic variable, while controlling for the psychological variables. They found that while gender was not significant in predicting WTP differences for CAV, they did find differences associated with the psychological factors. Their results suggested that compared to men, women would feel higher dread when thinking about riding in CAVs, which is in line with historical gender related findings in the psychology and behavioral science research. They found age to be a significant predictor of WTP; higher age decreased participants' WTP for CAVs, which was contrary to other studies. Also, income and education level were found to be positive predictors of WTP, while not necessarily associated with intention to use CAVs. Overall, they found that 26.3% of respondents had a WTP of $0, 39.3% were willing to pay up to $2900, and 34.3% were willing to pay more than $2900.

In contrast to the studies mentioned above, our review finds one study that applied conjoint analysis to measure WTP. As mentioned earlier, conjoint analysis is grounded in the assumption that money values (like WTP) cannot be measured directly, therefore the intention with this type of assessment is to decompose individual evaluations or discrete choices into money values. That is, the value is inferred based on the selections individuals make from a set of alternatives or ratings. While there are a number of different ways to perform conjoint analysis, the assessment generally requires the use of experimental design techniques (such as factorial design) to construct sets of choice alternatives, with multiple attributes per alternative. However conjoint analysis approaches differ in terms of response mode (survey question design), analysis methods, and inferences about recorded choice behavior (Louviere, 1988).

Daziano et al. (2016), is the only study found to apply conjoint analysis to measure WTP for CAVs, although the focus was on instead on autonomous electrical vehicles (AEVs) rather CAV's generally. The authors apply three different logit discrete choice models, all differing by how fuel cost is defined. They administered an online survey, which drew 1260 respondents. Demographic variables collected included age, gender, ethnicity, education level, employment status, and household size characteristics. One of their core advantages of their discrete choice approach was having full control over attributes of alternatives, which allows for the monetary value of these attributes (to consumers) to be assessed, even for products that are not fully available on the market (AEVs). Overall, they found that the average household was willing to pay $3500 for partial automation and $4900 for full automation.

2.4.Critique of Adoption Assessment Approaches

The first thing to notice is that equity implications are not considered in any of the previous studies. The core of our critique is that the approaches applied to assess adoption rates are not well suited to measure how adoption rates are likely to differ for transport disadvantaged communities. There are two primary reasons for this. First is related to the appropriateness of WTP measurement approaches implemented recent studies that have estimated CAV adoption. We also discuss the appropriateness of assessing the equity implications using WTP measures. The second is concerning the usefulness of current survey data for assessing differences in adoption rates.

First, the use of contingent valuation to estimate WTP measures may be introducing a bias that can be mitigated by a conjoint analysis approach. Magat et al. (1988) argued that the CV approach creates incentives for respondents to understate their true value, while the conjoint analysis approach eliminates the incentive, thereby producing more accurate WTP. In their comparison of CV and CA approaches, Boxall et al. (1996) found that CV results may be biased upward because respondents are typically not required to consider tradeoff or substitutions. While both CV and CA methods of eliciting WTP are subject to hypothetical bias (Loomis, 2014), CA still offers considerable conceptual enhancement over CV, as CA is able to generate a result closer to market reality (Boxall et al. 1996), and is more suitable for assessing products for which there is significant uncertainty (Grunert et al. 2009). As highlighted in section 2.3, few studies have applied conjoint analysis to estimate WTP. Although the accuracy of measures produced from conjoint analysis using discrete choice can be very sensitive to the model specification (Stevens et al. 2000), it offers clear conceptual advantages relative to contingent valuation.

Second, if WTP is to support critical market decisions (e.g. how to price and market CAV technologies), the practice of estimating WTP should be more comprehensive and less focused on preserving current market estimates. For example, a number of the studies described in section 2.3 estimate separate WTP values for various markets, including those with a WTP of $0, but few if any take the additional step of assessing the demographics or attitudes associated with this market segment. Further, several studies highlight that "experience" matters (Charness et al., 2018). Having heard of CAVs as well as having a higher level of autonomous vehicle technology on their current vehicle were associated with greater interest in autonomous vehicle technology. The study by Bansal and Kockelman (2017) suggests that respondents who had heard about google self-driving cars, had experience with speed governors on new vehicles, and with a higher VMT also had a higher WTP. Further, given that we can expect "awareness" and "exposure" to spread among the society over time, the consideration of these effects in estimating WTP will be more in line with the CAV-related market behavior of the future, as opposed to the existing behaviors. For these reasons, the estimation of WTP for CAVs should more uniformly consider "awareness" and "exposure" effects.

Third, WTP is likely to differ by ethnicity. A study by Duncan et al. (2015) found a range of demographic variables to be associated with people's opinion, comfort level and willingness to use CAV technology. They highlighted that Hispanics were more likely to exhibit more positive views towards CAVs., even after controlling for income level. Nevertheless, no recent study was found to consider ethnicity in estimating WTP for CAVs.

2.5. Critics of Available Survey Data

Recall from section 1.2 that in order to assess equity implications of CAV technologies it is necessary to compare impacts of transport disadvantaged communities relative to their more affluent counterparts. This means that variables for clearly defining these comparison groups must be available in the data, and therefore collected along with other survey questions. However, we find that the survey data collected for recent studies on the WTP for CAVs is uniformly under-representative of transport disadvantaged individuals, and few studies were found to attempt sample correction procedures (such a sample weighting). In particular, Bansal et al. (2016) indicated that their data overrepresented women, middle-aged persons between 25-44, and those with a bachelor's degree or higher. Other studies on public opinion on CAVs (such as Duncan et al., 2015) have managed to collect targeted samples of the elderly population (for example), nevertheless their respondents were also better educated and less diverse than the State population as a whole.

3. Methods of Forecasting Travel Behavior Changes due to CAVs

Questions of how travel behaviors are likely to change as a result of CAVs, has also seen significant attention in the literature. We find that a broad range of approaches have been applied to assessing how travel behaviors are likely to change as a result of CAVs. These include field surveys/experiments and driving simulators on one end of the spectrum and fine-grain predictive modeling (like activity based travel demand modeling) on the other end. For this portion of the review, we focus on two areas. The first relates to approaches that are dependent on the collection of empirical survey data in some way. These include field experiments and surveys, driving simulators, and travel demand models. The second area relates to approaches that depend on forecasting and or hypothetical scenario analysis. This also includes travel demand models, as they are estimated using empirical survey data and involve forecasting behavioral trends based on projections of land use and population change. This second group also includes stated preference surveys. While stated preference surveys also require participant recruitment, they record the choices, attitudes, and opinions of respondents under hypothetical scenarios.

A number of studies have applied field surveys and live experiments to explore likely changes in travel behavior as a result of CAVs. Virtually all surveys related to this topic can be classified as stated preference surveys, as they seek to elicit thoughts and opinions about new transportation technologies that are not fully available in the market. These studies have focused on a range of travel behaviors including use of in-vehicle travel time, and amount of travel (VMT).

Examples of these studies focusing on in-vehicle travel time include Schoettle and Sivak (2014) and Bansal and Kockelman (2018). Using a survey of 3255 respondents from the US, Australia, and the UK, Schoettle and Sivak (2014) assessed respondents' opinions related to whether and how respondents would make use of CAVs. The general assumption regarding in-vehicle time use is that because travelers would not be driving themselves, their time could be spent more productively (Sivak and Schoettle, 2016). Additional demographic variables collected in the survey include age, gender, education, and employment status. Their results suggest that for those who would use a CAV (77.6% of the total sample), a large share of travelers (41%) would continue to watch the roads, while some would take the time to read/work or text/talk over the phone (14.2% and 7.7% respectively). Some would use the time to sleep (7%), while the remaining (7.7%) would mostly use the time to enjoy TV/movies or video games. Bansal and Kockelman (2018) conducted a comparable survey of 1088 residents of Austin, TX. They found that of those who expressed interest in riding in CAVs (71.5% of respondents), the most popular responses on in-vehicle time use were talking to other passengers (59.5%) and looking out the window (59.4). Important demographic variables collected in the survey include age, gender, ethnicity (including White, European white, or Caucasian option, only), education, income, and a range of household size characteristics.

The range of approaches have been applied to assessing how vehicle miles traveled (VMT) may be affected by CAV use, with field studies on one hand and travel demand modeling on the other. One paper (Harb et al., 2018) was found that applied a field experiment approach. They implemented a realistic experiment to project a sample of travelers into a world of self-driving cars. In this pilot version of a larger anticipated study, they provided 60 hours of free chauffeuring service for a sample of 13 participating households, over a 7-day period. Important demographics collected from participants include age, gender, generation cohort (i.e. millennials vs. families vs. retirees), and income level. Overall, the study found that the free chauffeuring service led to a 83% increase in VMT.

Studies that have applied virtual reality and driving simulations to assess potential changes in travel behavior include Jamson et al. (2013). In response to questions of driver situation awareness in CAVs, this study examined multitasking behaviors of a sample of 49 drivers using a high-fidelity driving simulator. Their simulator allowed participants to experience through seeing, hearing and, feeling what it would be like to handle an autonomous vehicle. They found that participant drivers tended to refrain from behaviors that required them to retake control of the vehicle (such as over taking), which resulted in increases in travel times.

A number of studies applied travel demand models to assess the potential for various travel behavior changes. An example of this is a study by Childress et al (2015). They use an activity-based travel demand model, estimated for the Seattle, WA metro region, to assess potential changes in travel behavior. Based on an analysis of four different scenarios, their results suggest that efficiency improvements in roadway capacity and the quality of driving may result in increases in VMT ranging from 8% to 24% (depending on assumptions of how the traveler's value of time may change). Their results show that this would in part be due to travelers switching modes from transit and walking modes to single occupancy CAVs (9% and 21% respectively). A study by Levin and Boyles (2015) applies a multiclass, four-step travel demand model to investigate repositioning behaviors to avoid parking fees. That is, their model simulates the effect of vehicles that drop off travelers at their destination and return to pick them up. Their results suggest that VMT from personal trips would sharply increase by 271.4% as a result of repositioning.

One study (Cohn, et al. 2019) was found that focused on assessing the equity implications of CAVs using a travel demand model. This study applied a regional 4-step travel demand model to assess how job accessibility, trip duration, trip distance, mode share, and VMT would change for transport disadvantaged communities in Washington, DC, in comparison to more affluent groups. The study assess 8 different planning scenarios and their results suggest that while VMT increases would likely be higher for equity-emphasis areas, the scenario including high-occupancy (shared) CAVs and enhanced transit alternatives provided an equity benefit by either mitigating the existing gap in benefits between comparison groups or reducing the degree of growth in the gap.

3.1. Critique of Methods of Forecasting Travel Behavior Changes due to CAVs

Similar to the first portion of this review, very few studies mention any equity implications of travel behavior changes due to CAVs, and only one study was found to focus explicitly on assessing the equity related effects associated with future CAV use. We have two primary critiques on the above literature. First is that the usefulness of these approaches are most likely conditioned on the sampling and recruitment strategies for participants. All approaches that have been applied for exploring travel behaviors of CAV use depend on some form of observed empirical data or survey participant recruitment. Therefore the usefulness of these methods for assessing equity implications will depend on how well survey datasets are representative of transport disadvantage communities as well as the extent that relevant demographic data are collected from survey/experiment participants, for defining transport disadvantage communities. Second is that more fine-grain models of travel demand, such as activity-based models, are critical for a more meaningfully understanding of equity implications of CAV, as they allow for individual and household level equity measures to be estimated and assessed. Traditional four-step travel demand models are only capable of zonal level group segmentation of households, which can lead to significant aggregation biases for transportation equity analyses (Castiglione et al., 2006; Bills and Walker, 2017). To date no studies have been found to have applied activity-based travel demand models to assess the equity implications of CAVs.

4. Broad and Longer-terms Effects of Travel Behavior

The group of questions that are arguable most relevant to understanding the equity implications of CAVs, are related to the broad and longer term effects that may result from CAV adoption and changes in travel behaviors. These include potential changes in the cost of transportation (e.g. vehicle operating costs, transit fares, energy costs, and parking costs), accessibility, land-use related changes (e.g. reductions in parking space), emissions from transportation, and more. A number of studies are found that have focused on assessing such broad and longer term effects of CAVs implementation. As these effects are closely tied to adoption rates and travel behavior changes due CAV implementation, the range of methods that have been applied to assessing these effects follow after those used for assessing travel behavior and travel choice related changes, with adoption rates specified as endogenous inputs. Some studies implement more conventional 4-step travel demand models, while other implement macroscopic transportation, and land-use models. Examples of these studies include Gelauff et al. (2017), Meyer et al., (2017), Zhao and Kockelman (2018), and Cohn, et al. (2019). Gelauff et al. (2017) applied a landuse-transportation interaction model for assessing potential population concentration and dispersion, as well as residential land prices in the Netherlands. Meyer et al., (2017) applied the Swiss National Transport Model, a macroscopic transport model, to assess the long terms accessibility changes due to future CAV use. They find that accessibility, as indicated by a gravity-based employment accessibility measure, is likely to increase significantly, by as much as 10%. Finally, Zhao and Kockelman (2018) applied a conventional travel demand model, estimated for the Austin, TX metro region. They investigated the effects of CAVs as well as shared-autonomous vehicles on a range of potential outcomes, including travel distance and transit mode share. Overall, their results suggest that there would be increases in the demand for longer distance travel and reductions in transit system use.

4.1. Equity implications of Broad and Longer-term Effects of CAV Travel behavior

Given the similarity of methods and approaches for assessing broad and longer term effects of CAV travel behavior, our critique from section 3.1 holds here as well. Cohn, et al. (2019) is the only paper found to have applied a form of travel demand model for assessing longer term (job-accessibility) equity implications of future CAV use. Further, the various types of travel or land-use-related models likely depend on standard travel diary surveys and other empirical input data that are under-representative of transport disadvantage communities, limiting their usefulness for assessing equity implications.

5. Conclusions

This review focuses on summarizing the state of methods available for measuring the equity implications of future connected and autonomous vehicle use. It is clear that few studies have focused on assessing equity implications of CAVs to date, however a number transportation planning and policy thought leaders have expressed concern for the equity outcomes of implementing CAVs. Litman (2017) listed “Social Equity Concerns” as a clear concern of implementing CAVs. Other reports indicate that equity is receiving some attention from planning organizations (Kuzio (2019), and a clear outline is beginning to emerge on what the broader equity implications of CAVs may be (Ricci, 2019).

Our review finds that while a range of methods exists that may be applied to begin building our understanding of CAV equity implications, clear guidance how to appropriately apply these is warranted. Regarding CAV adoption, it is certainly possible to estimate WTP for transport disadvantaged groups, but important demographic variables for defining transport disadvantaged groups are not uniformly collected in the survey data, nor are previous surveys collected sufficiently representative of transport disadvantaged groups. Regarding modeling approaches for assessing travel behavior changes, they are subject to similar challenges with data representation, as they are estimated using empirical survey data and other inputs. Further, the only study to have assessed travel behavior related equity implications, applied a conventional 4-step travel demand model, which is not capable of more fine-grain (individual level) measures of equity. This calls into question the usefulness of these approaches for meaningful equity analysis. The use of an activity-based or other agent based travel model is likely to produce more useful results.

6. References

Bansal, P., Kockelman, K. M., & Singh, A. (2016). Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transportation Research Part C: Emerging Technologies*, *67*, 1-14.

Bansal, P., & Kockelman, K. M. (2017). Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. *Transportation Research Part A: Policy and Practice*, *95*, 49-63.

Bansal, P., & Kockelman, K. M. (2018). Are we ready to embrace connected and self-driving vehicles? A case study of Texans. *Transportation*, *45*(2), 641-675.

Bills, T. S., & Walker, J. L. (2017). Looking beyond the mean for equity analysis: Examining distributional impacts of transportation improvements. *Transport Policy*, *54*, 61-69.

Boxall, P. C., Adamowicz, W. L., Swait, J., Williams, M., & Louviere, J. (1996). A comparison of stated preference methods for environmental valuation. *Ecological economics*, *18*(3), 243-253.

Breidert, C., Hahsler, M., & Reutterer, T. (2006). A review of methods for measuring willingness-to-pay. *Innovative Marketing*, *2*(4), 8-32.

Cassetta, E., Marra, A., Pozzi, C., & Antonelli, P. (2017). Emerging technological trajectories and new mobility solutions. A large-scale investigation on transport-related innovative start-ups and implications for policy. *Transportation Research Part A: Policy and Practice*, *106*, 1-11.

Castiglione, J., Hiatt, R., Chang, T., & Charlton, B. (2006). Application of travel demand microsimulation model for equity analysis. *Transportation Research Record: Journal of the Transportation Research Board*, (1977), 35-42.

Charness, N., Yoon, J. S., Souders, D., Stothart, C., & Yehnert, C. (2018). Predictors of attitudes toward autonomous vehicles: the roles of age, gender, prior knowledge, and personality. *Frontiers in psychology*, *9*, 2589.

Childress, S., Nichols, B., Charlton, B., & Coe, S. (2015). Using an activity-based model to explore the potential impacts of automated vehicles. *Transportation Research Record*, *2493*(1), 99-106.

Cohen, S., Shirazi, S., & Curtis, T. (2017). Can We Advance Social Equity with Shared, Autonomous and Electric Vehicles?. *Institute of Transportation Studies at the University of California, Davis*.

Daziano, R. A., Sarrias, M., & Leard, B. (2017). Are consumers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *78*, 150-164.

Di Ciommo, F., & Shiftan, Y. (2017). Transport equity analysis.

Duncan, M., Charness, N., Chapin, T., Horner, M., Stevens, L., Richard, A., ... & Morgan, D. (2015). Enhanced mobility for aging populations using automated vehicles (No. BDV30 977-11). Florida. Dept. of Transportation.

Gelauff, G., Ossokina, I., & Teulings, C. (2017). Spatial effects of automated driving: Dispersion, concentration or both. The Hague: KIM – Netherlands Institute for Transport Policy Analysis

Grunert, K. G., Juhl, H. J., Esbjerg, L., Jensen, B. B., Bech-Larsen, T., Brunso, K., & Madsen, C. O. (2009). Comparing methods for measuring consumer willingness to pay for a basic and an improved ready made soup product. *Food Quality and Preference*, *20*(8), 607-619.

Harb, M., Xiao, Y., Circella, G., Mokhtarian, P. L., & Walker, J. L. (2018). Projecting travelers into a world of self-driving vehicles: estimating travel behavior implications via a naturalistic experiment. *Transportation*, *45*(6), 1671-1685.

Jamson, A. H., Merat, N., Carsten, O. M., & Lai, F. C. (2013). Behavioural changes in drivers experiencing highly-automated vehicle control in varying traffic conditions. *Transportation research part C: emerging technologies*, *30*, 116-125.

Just, R. E., Hueth, D. L., & Schmitz, A. (2005). *The welfare economics of public policy: a practical approach to project and policy evaluation*. Edward Elgar Publishing.

Kuzio, J. (2019). Planning for social equity and emerging technologies. *Transportation research record*, *2673*(11), 693-703.

Levin, M. W., & Boyles, S. D. (2015). Effects of autonomous vehicle ownership on trip, mode, and route choice. *Transportation Research Record*, *2493*(1), 29-38.

Litman, T. (2002). Evaluating transportation equity. *World Transport Policy & Practice*, *8*(2), 50-65.

Litman, T. (2017). *Autonomous vehicle implementation predictions* (p. 28). Victoria, Canada: Victoria Transport Policy Institute.

Liu, P., Guo, Q., Ren, F., Wang, L., & Xu, Z. (2019). Willingness to pay for self-driving vehicles: influences of demographic and psychological factors. *Transportation Research Part C: Emerging Technologies*, *100*, 306-317.

Loomis, J. B. (2014). 2013 WAEA keynote address: Strategies for overcoming hypothetical bias in stated preference surveys. *Journal of Agricultural and Resource Economics*, 34-46.

Louviere, J. J. (1988). Conjoint analysis modelling of stated preferences: a review of theory, methods, recent developments and external validity. *Journal of transport economics and policy*, 93-119.

Magat, W. A., Viscusi, W. K., & Huber, J. (1988). Paired comparison and contingent valuation approaches to morbidity risk valuation. *Journal of Environmental Economics and Management*, *15*(4), 395-411.

Marder, E. (1999). The assumptions of choice modelling: Conjoint analysis and SUMM. *Canadian Journal of Marketing Research*, *18*, 3-14.

Martens, C. J. C. M. (2006). Grounding transport planning on principles of social justice.

Metropolitan Transportation Commission (2001), The 2001 Regional Transportation Plan Equity Analysis and Environmental Justice Report.

Metropolitan Transportation Commission (2013), Draft Equity Analysis Report. 2013

Retrieved from: https://www.planbayarea.org/sites/default/files/pdf/Draft_Plan_Bay_Area/Draft_Equity_Analysis_Report.pdf (MTC, 2013a)

Musgrave, R., Musgrave, P.P. (1989) Public Finance in Theory And Practice. International Edition McGraw-hill Book Company.

NHTSA [National Highway Traffic Safety Administration]. (2013). Preliminary statement of policy concerning automated vehicles. Available at: http://www.nhtsa.gov/staticfiles/rulemaking/pdf/Automated_Vehicles_Policy.pdf

Nordhoff, S., van Arem, B., & Happee, R. (2016). Conceptual model to explain, predict, and improve user acceptance of driverless podlike vehicles. *Transportation research record*, *2602*(1), 60-67.

Ricci, A. (2019). Socioeconomic Impacts of Automated and Connected Vehicle: Summary of the Sixth EU–US Transportation Research Symposium. In *Transportation Research Board Conference Proceedings* (No. 56).

Rodier, C. J., Abraham, J. E., & Tonkin, G. J. (2001). *Applying an Integrated Model to the Evaluation of Travel Demand Management Policies in the Sacramento Region*. Mineta Transportation Institute, San José State University.

San Diego Association of Governments (SANDAG) (2011). 2050 Regional Transportation Plan. <http://www.sandag.org/uploads/2050RTP/F2050rtp_all.pdf>

Schoettle, B., & Sivak, M. (2014). *A survey of public opinion about autonomous and self-driving vehicles in the US, the UK, and Australia*. University of Michigan, Ann Arbor, Transportation Research Institute.

Sivak, M., & Schoettle, B. (2016). Would self-driving vehicles increase occupant productivity. *Sustainable Worldwide Transportation, The University of Michigan, Ann Arbor, http://umich. edu/~ umtriswt/PDF/SWT-2016–11_Abstract_English. pdf, accessed*, *20*.

Stevens, T. H., Belkner, R., Dennis, D., Kittredge, D., & Willis, C. (2000). Comparison of contingent valuation and conjoint analysis in ecosystem management. *Ecological economics*, *32*(1), 63-74.

Vlassenroot, S., and K. Brookhuis. Socio-Psychological Factors That Influence Acceptability of Intelligent Transport Systems: A Model. In Driver Acceptance of New Technology: Theory, Measurement, and Optimization (M.A. Regan, T. Horberry, and A. Stevens, eds.), ARRB Group Limited, Vermont South, Victoria, Australia, 2014, pp. 35–50.

Zhao, Y., & Kockelman, K. M. (2018). Anticipating the regional impacts of connected and automated vehicle travel in Austin, Texas. *Journal of Urban Planning and Development*, *144*(4), 04018032.